WAVELET TRANSFORM IN INVESTIGATIONS OF STUDENTS EDUCABILITY DEPENDENTLY ON DEGREE OF GRAFICAL SKILLS AUTOMATION OF WRITING PROCESS

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Abstract: Application of 2-level 2-D Haar Discrete Wavelet Transform of images with special words repeated by hand is offered. Metric of similarity for images with pattern words and images with students' written words like analog of proposed patterns is considered. A new approach to objective assessment of educability like dependence on level of graphic skills of process of writing is offered. Experiment is revealed the presence of statistic significant correlation between average score in special academic subjects group or in other words between special educability and level of graphic writing skills automation for high school students.

Keywords: educability, process of writing, 2-D discrete wavelet transform, image similarity

ACM Classification Keywords: I.5 PATTERN RECOGNITION and K.3.2 COMPUTER AND INFORMATION SCIENCE EDUCATION

1 The degree of automation of movements in writing process like a feature of the higher nervous activity

Process of writing is a complex activity and all divisions of the cerebral cortex participate in its formation. Psychophysical basis of process of writing is the interaction of different analyzers – speech-motor, auditory, visual, hand-motor. The interaction of such mental activities as thinking, memory, attention, imagination, external and internal speech occurs during writing. Process of writing is a complex motor skill, which includes technical, graphical and spelling skills. Graphic skills reflect the ability to write symbols by hand on paper quickly and clearly and spelling skills reflect knowledge how to apply hand-written characters and the abilities to use these rules during process of writing for the reflecting of its content. Technical skill is manifested in the ability to hold the right techniques and methods of writing, such as proper position of the body during process of writing or the location of paper, etc. The technical and graphic skills define a character and features of the handwriting of a person.

The process of writing according to its psychological content from the outset is a conscious act to be formed in the special education arbitrarily and requires a number of special operations for its implementation in contrary to spoken language which assimilated across the imitating of another person's speech.

The type of coordination of movements during process of writing that acquired in learning and the degree of automation of these movements greatly influence on the number and nature of deviations appeared during writing, from the typical patterns of writing of characters and symbols. Insufficient degree of automation of movements during process of writing will be manifested in significant changes in the implementation of characters and their compounds than it is happening in the cases with a sufficient degree of automation of these movements [Kornev 1999, Bernstein 1990].

Processes of excitations and inhibitions are main nervous processes taking place in development of writing. Ratio of the basic properties of these processes (power, balance, mobility) affects the formation of writing. Type of higher nervous activity, depending on the degree of dominance first or second signaling system in it and the

degree of precision transfer of temporal links the first signaling system in the second one, which may be different for individuals, may affect the ability of that person more or less successfully imitate of handwriting features of another person. I. Pavlov identifies three main types of people depending on the predominance of the first or second signal system in the brain [Bernstein 1990]:

a) the artistic style, characterized by a predominance of the first signaling system;

b) the thinking style, characterized by a predominance of the second signaling system;

c) the average type, characterized by a relative balance of both signaling systems.

Other things being equal, person with a predominance of the first signaling system in the state more accurately imitate the handwriting of another person and demonstrate in his process of writing to the significant set of handwriting features of another person than those with a predominance of the second signal system. It is known that persons with a more precision transfer of temporal links the first signaling system in the second signaling system able to fully and comprehensively recognize the signs of his and others' handwriting and successfully imitate the handwriting of another person [Kornev 1999].

Thus, individual differences in process of writing to different persons are a reflection not only of external learning environments, but also characteristics of their higher nervous activity.

2 organization of the experiment to identify the statistical relationship between educability and the level of graphical skills automation of writing process

Pavlov's research showed that education is the formation of temporary connections in the cerebral cortex of the brain, and skill – the system of these bonds [Podlasiy 2003].

On the one hand, the motor component of process of writing requires considerable conscious effort and attention when writing, distracting him from more important tasks associated with given semantic task. On the other hand, it's known that productivity of education is directly proportional to level of educability and stability of attention of students, and it also depends on the level of their memory. Addition, the student achievements are directly proportional to educability depending on the strength of attention. Therefore, if we assume that student estimations reflect student's achievements and student with higher scores has greater educability, then the level of automation of the motor components of process of writing is a reflection of the level of attention, therefore, the level of educability that is the main hypothesis will be tested experimental.

Distinguish between general educability – the ability of mastering any material and special educability – learning ability of certain types of material (of various sciences, academic subjects, practices). The first type of educability is an indicator of the total talents of the individual while the second one is an indicator of only special.

To identify the statistical relationship between each type of educability and the level of graphical skills of writing process works from 18 third-year students of Computer and Information Technologies Faculty in the National technical university «Kharkiv Politechnical Institute» (Ukraine) were analyzed. Forms with patterns of words with different lengths in native language were given for students in several weeks. One part of such sheets is shown in Figure1a.

Spelling and fonts of handwriting patterns are conform to the norms of the Ministry of Education and Science of Ukraine and were taken from handwriting patterns for primary classes. Students were not aware of the purpose of the experiment, in other words they were not aware that the quality of this works will be compared with their educability. For students the problem had formulated such: as precisely as possible to repeat the handwriting patterns of words and to continue write to string the same words in the shortest time. Then an average score was

calculated from previous 4 sessions for each student. Moreover, all subjects were divided into two groups – the general and special subjects. Each group of academic subjects is corresponds to general or special educability.

a
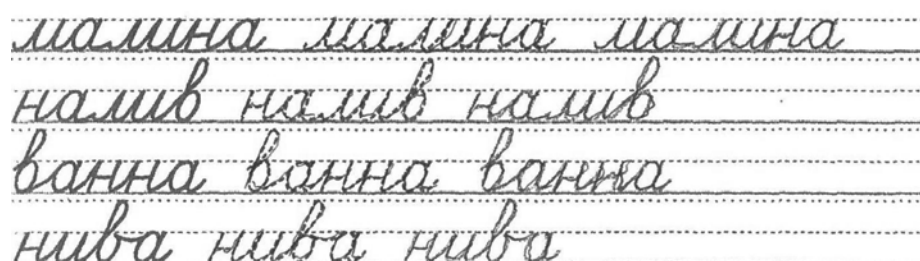
b

Fig.1. Examples of experimental materials: a – part of a sheet-pattern, b – part of a sheet-result

Table 1. Groups of academic subjects

General subjects	Special subjects
High Mathematics	Programming
Ukraine History	Basics of Computer Technology
Physics	Computer-aided design
Engineering Graphics	Discrete Mathematics
Theory of electro-magnetic circuit	System Programming
Philosophy. Logic	Applied theory of digital automata
Foreign Language	Computer electronics and circuitry
History of Science and Technology	Computing Algorithms and Data Structures
Cultural Studies, Ethics , Religious studies	Databases
Sport	Computers Architecture

Thus, the level of automation of graphical and motor skills of process of writing reinforced by the ability to properly carry out the assigned trivial tasks are compared with two values of average scores on general and special academic subjects.

3 Processing of experimental data

20 repeated and 20 own written three-, four- and five-symbols words for each student were selected from all obtained materials. To assess the level of graphical skills automation of writing process measure of similarity between the proposed handwriting patterns of word and both repeated word and own written same word are analyzed. Digital variants of experiment materials was received by scanning of the completed student sheets with experimental results and clean patterns sheets with same resolution. Algorithm for primary processing of digital images has been developed and implemented in Matlab. The sense of the algorithm is as follows:

- alignment of contours on patterns sheets and results sheets;

- subdividing of whole sheets on disjoint sub-images with patterns of every words;

- select a base point on the processed results sheet which will be left down vertex of the allocated area of interest with equal size dimensions to pattern sub-image of corresponding word (Figure 2);

- convert the result sub-image with analyzed word into grayscale.
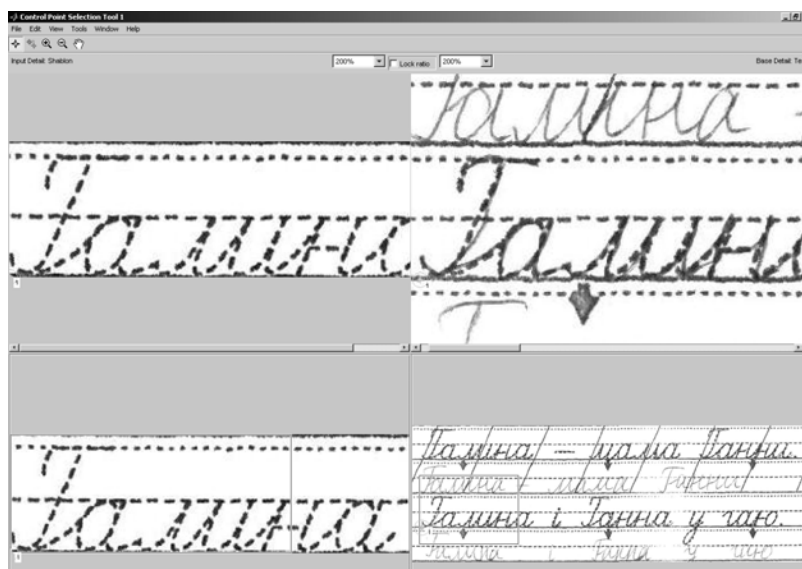

Fig. 2. Selection of interest area into results sheet

After primary processing the task of experiment results processing are considered as a problem of quantitative comparison of pattern and result sub-images with corresponding word through a specific metric called similarity measurement. A high similarity value between two images means a high level of graphical skills automation of writing process.

To images recognizing and to their similarity estimation Fourier Transform and discrete wavelet transform are successfully used [Bebis 2006, Pretto 2010, Rakhmankulov 2008].

As presented in [Burrus 1998] the Fourier Transform gives the spectral content of the whole signal, but it gives no explicit information regarding where in space those spectral components appear. A better tool for non-stationary signal analysis (whose frequency response varies in time, like in the images) is the Wavelet Transform [Iyengar 1997, Chui 1992, Mallat 1998]: it gives information about which frequency components exist and where these components appear. Properties of Discrete Wavelet Transform (DWT) coefficients were exploited in order to calculate the images similarity for our case. Every image can be represented as a linear combination of the images in the wavelet basis:

$$P(x) = \sum_{k} c_k \varphi_k(x) + \sum_{k} \sum_{j} d_{j,k} \psi_{j,k}(x) \tag{1}$$

where c_k – approximation coefficients, $d_{j,k}$ – detailed coefficients, k – location index, j – scale parameter.

A wavelet representation of a function consists of a coarse overall approximation together with detail coefficients that influence the function at various scales. For our experiment 2-D Haar DWT of the grayscale images was selected. Given the resolution of images, we decide to stop at second level of decomposition.
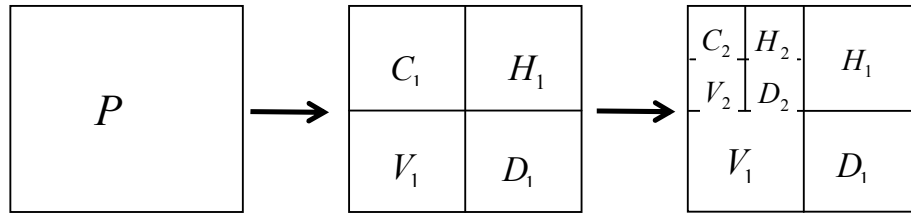

Fig.3. Two-level 2-D Wavelet decomposition

2-level 2-D Wavelet decomposition of input image P_i, and C_j – the approximation coefficients, H_j, V_j, D_j – respectively the horizontal, vertical and diagonal detailed coefficients in j-th level of the wavelet decomposition are shown in Figure 3. Transform going to higher level decompositions can significantly reduce the decomposed image's size, but higher level of decompositions discard important features in images, like edges and high frequency patterns useful for comparing of images in our experiment.

The Haar Wavelet is chosen as a wavelet type because of it is very effective in detecting the exact locations when a signal changes: image discontinuity is one of most important features chosen in image-based localization. The detail coefficients are the intensity variations along rows, columns and diagonals. Thus detailed coefficients can be used to detect and highlight image shapes. The higher the absolute values of coefficients are the higher probabilities that it encodes salient image features.
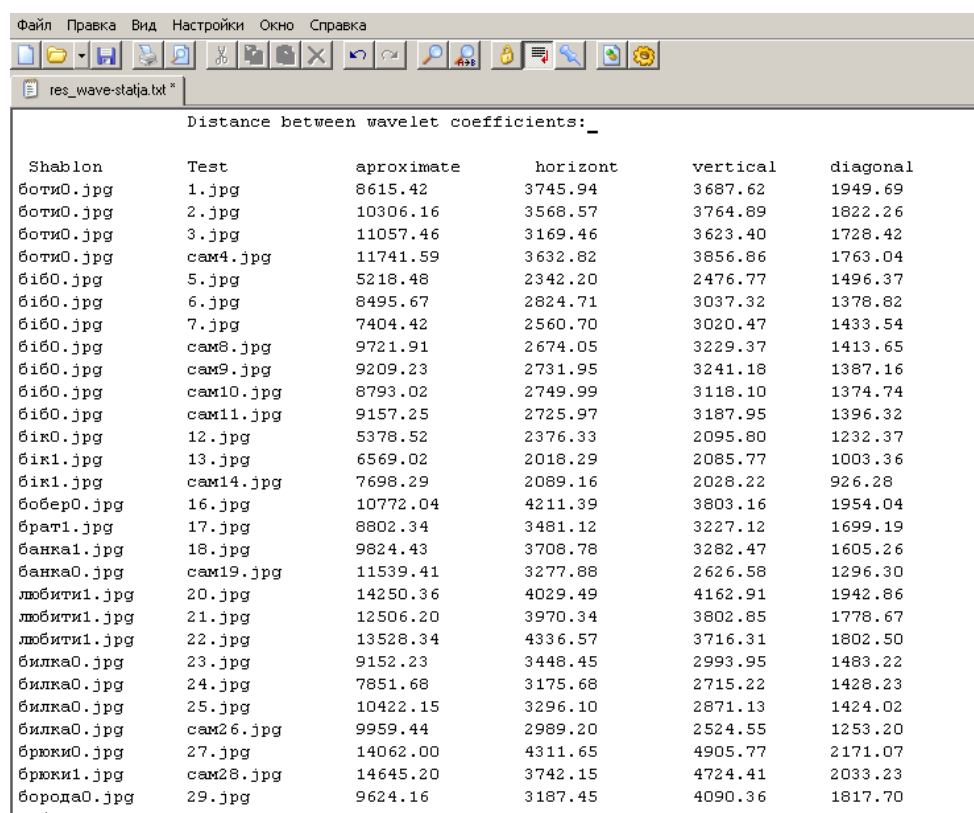
2 sets of 4 matrices of the horizontal, vertical and diagonal detailed coefficients with dimensions $a \times b = w/2^{wavelet\,....level} \times h/2^{wavelet\,....level}$ where w is the image's width and h is the image's height were obtained by using the functions from Matlab to calculate the coefficients of 2-level 2-D Haar DWT for each pair of pattern-result sub-images.

A metric that compares how many significant wavelet coefficients the query has in common with potential targets is used to compute image similarity usually [Pretto 2010]. But in our case, such a metric is not suitable, especially for the analysis of the repeated handwriting words. Therefore, considering the obtained matrix with coefficients as coordinates of multidimensional space, calculate the length of each vector $\rho(C_2), \rho(H_2), \rho(V_2), \rho(D_2)$ by the formula calculating the Euclidean distance between the coordinates of wavelet coefficients space for pattern and result sub-images with corresponding word:

$$\rho(C_2) = \sqrt{\sum_{l=1}^{a}\left(C_2^{sh}(l)-C_2^{t}(l)\right)^2 + \sum_{c=1}^{b}\left(C_2^{sh}(c)-C_2^{t}(c)\right)^2},$$

$$\rho(H_2) = \sqrt{\sum_{l=1}^{a}\left(H_2^{sh}(l)-H_2^{t}(l)\right)^2 + \sum_{c=1}^{b}\left(H_2^{sh}(c)-H_2^{t}(c)\right)^2},$$

$$\rho(V_2) = \sqrt{\sum_{l=1}^{a}\left(V_2^{sh}(l)-V_2^{t}(l)\right)^2 + \sum_{c=1}^{b}\left(V_2^{sh}(c)-V_2^{t}(c)\right)^2},$$

$$\rho(D_2) = \sqrt{\sum_{l=1}^{a}\left(D_2^{sh}(l)-D_2^{t}(l)\right)^2 + \sum_{c=1}^{b}\left(D_2^{sh}(c)-D_2^{t}(c)\right)^2}$$

(2)

where sh – index of matrixes' elements for approximation coefficients, for horizontal, diagonal and vertical detailed coefficients of second level wavelet decomposition of pattern sub-image, respectively,

t – index of matrixes elements for approximation coefficients, for horizontal, diagonal and vertical detailed coefficients of second level wavelet decomposition of result sub-image, respectively.

Fig.4. Example of part of results sub-images processing for one student

An example of the file with obtained according to (2) distances $\rho(C_2), \rho(H_2), \rho(V_2), \rho(D_2)$ between all pattern and result sub-images accordingly for one student are shown on Figure 4. Left two columns contain the

names of files with compared sub-images and the next 4 columns contain $\rho(C_2), \rho(H_2), \rho(V_2), \rho(D_2)$ respectively. Obtained distances were grouped in 3 samples, depending on the length of the word-pattern. For each sample were calculated standard deviations.

Standard deviation of the distance between the corresponding wavelet coefficients of pattern and result sub-images was calculated for each length of word. Correlation coefficients between the average score of general and special subjects groups disjoint and standard deviations of distances between 2D Haar DWT coefficients for every lengths of word were calculated in Statgraphics Centurion package.

Each line in Figure 5 contains data of one student in the following sequence: average scores on special academic subjects, standard deviations of $\rho(C_2), \rho(H_2), \rho(V_2), \rho(D_2)$ for three-symbol words and standard deviations of $\rho(C_2), \rho(H_2), \rho(V_2), \rho(D_2)$ for four-symbol words.

Pearson product moment correlations between each pair of variables x and y calculated by:

$$r(x, y) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (3)$$

are represented in Table 2. P-values below 0,05 indicate statistically significant non-zero correlations at the 95,0% confidence level.

	спец	грубо_3	гориз_3	верт_3	диаг_3	грубо_4	гориз_4	верт_4	диаг_4
1	4,83	1194,02	439,05	561,85	239,26	2145,62	679,94	590,67	238,04
2	3,42	760,3	223,38	442,38	140,19	2061,16	428,48	353,68	167,77
3	5	1227,98	495,01	544,02	272,92	2424,39	840,04	557,34	319,89
4	4,67	841,51	329,83	636,22	244,39	2117,81	575,16	622,86	260,07
5	3	1258,43	284,65	668,9	253,95	2317,81	577,11	827,31	351,84
6	3,33	790,02	337,19	636,84	306,53	1180,54	483,32	595,34	360
7	4,92	1186,78	309,01	568,41	223,09	2131,3	574,97	475,11	216,45
8	4,92	934,65	212,32	464,89	216,27	933,71	477,81	637,17	298,74
9	4,42	1002,49	311,86	370,53	159,45	1190,23	377,04	370,37	189,53
10	5	1562,49	444,17	622,68	251,61	2326,5	652,11	656,41	358,24
11	4,17	1039,65	341,09	473,43	209,96	901,87	456,97	453,51	245,6
12	3,08	1152,57	349,68	445,7	195,27	1126,52	460	506,29	217,11
13	3,67	821,95	358,6	405,8	236,65	1463,19	607,86	608	430,65
14	3,25	1433,51	478	665,72	354,18	1594,81	718,66	748,88	528,68
15	4,58	1386,64	382,1	617,09	263,04	2331,69	735,44	668,18	342,39

Fig.5. Initial data for calculations of correlation coefficients

Table 2. Correlation coefficients between variables x and y

Number of symbols into word	Correlation coefficients $r(x,y)$				
	x	Group of academic subjects or educability type			
	Type of vector	y special	P-value	y general	P-value
3	$\rho(C_2)$	0,4752	0,0539	0,3952	0,1164
3	$\rho(H_2)+\rho(V_2)+\rho(D_2)$	0,1459	0,5764	0,0382	0,8842
4	$\rho(C_2)$	0,5552	0,0207	0,6807	0,0026
4	$\rho(H_2)$	0,5318	0,0280	0,4174	0,0955
5	$\rho(C_2)$	0,6905	0,0022	0,6228	0,0076
5	$\rho(H_2)+\rho(V_2)+\rho(D_2)$	0,3418	0,1793	0,5378	0,0260

4 Interpretation of results and future works

Considering the Haar Wavelet, the approximation coefficient C_2 represent only the mean of the intensity of the pixels composing the macro-squares (4x4 pixels in our case) or general characteristic of a word. On the other hand, the difference between values of this coefficient for pattern and result sub-images is proportional to the number of pixels which involved to writing of analog of the pattern word but have distinct intensities of pixels at the pattern word or to general recognition, the readability of the word.

The horizontal, vertical and diagonal detailed coefficients H_2, V_2, D_2 are shown preferential direction of inaccuracies in the writing of words. Since the maximum value correlation coefficient between $\rho(H_2)$ and the average score in special academic subjects group for 4-synbols words (r = 0.5318) with no statistically significant correlation with $\rho(V_2)$ (r = 0.2389 and P-value = 0.3558) demonstrates that the loss of attention during process of writing leads to more extreme variations in the width of written word than variations of its height .

Absence statistically significant correlation coefficients between the mean scores for both groups of subjects and three-symbols words requires further study and may be explained by the fact that when writing of short words "truncated" motor skills are predominated in nervous activities of students, similar to the graphical skills of alone symbol writing. Movements of hand in such cases are minimum also and do not require a long and precise control of motor skills. Besides shorter words easier to remember, that is why smaller loss of attention occurs during process of writing short words. This gives rise to the formation of hypotheses about the higher values of correlation coefficients between special educability and measures of patterns-results sub-images similarity for seven-, eight- or nine-symbols words. Verifying this assumption, as well as the formulation of regression models of students' educability relating to the level of graphical skills automation of students will be the subject of future studies.

Conclusion

Thus, described experiments revealed the presence of statistic significant correlation between average score in special academic subjects group or in other words between special educability and level of graphic writing skills automation for high school students. Further study about abilities of using 2-D Discrete Wavelet Transform to quantify the level of graphic skills automation of writing process should give base for models of an objective assessment of educability.

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